

DEEP LEARNING-BASED SPECTRUM SENSING AND DYNAMIC SPECTRUM ALLOCATION FOR 6G NETWORKS

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Abstract

The rapid growth of immersive applications, massive Internet of Things (IoT) connectivity, intelligent transportation, and ultra-reliable services in 6G networks increases demand for radio spectrum. Conventional static allocation cannot adequately utilize spectrum that remains temporarily unused, while conventional sensing techniques experience performance degradation under low signal-to-noise ratio (SNR), noise uncertainty, fading, and rapidly changing channel conditions. Recent studies indicate that deep learning can improve spectrum sensing by learning discriminative signal characteristics directly from received observations. Existing approaches generally address spectrum sensing and spectrum allocation as separate tasks, which can limit their responsiveness to instantaneous spectrum occupancy and traffic conditions. This study proposes a novel Deep Adaptive Spectrum Sensing and Allocation Network (DASSAN) that integrates a CNN-BiLSTM feature-learning module with an attention mechanism for spectrum occupancy detection and a deep reinforcement learning allocator for dynamic channel selection. The CNN extracts local spectral features, while BiLSTM captures temporal channel occupancy patterns. The attention mechanism emphasizes informative features, and the reinforcement-learning agent jointly considers spectrum availability, interference, traffic demand, and channel quality to select allocation decisions. The integrated framework is designed to improve sensing reliability, spectrum utilization, throughput, and allocation adaptability in dynamic 6G environments. The simulated results show that DASSAN achieves 99.1% accuracy, 99.3% detection probability, 3.4% false alarm rate, 128.3 Mbps throughput, and 95.8% spectrum utilization at 20 dB SNR. At 0 dB, it achieves 93.1% accuracy, 95.1% detection probability, 6.4% false alarm rate, 71.9 Mbps throughput, and 83.9% spectrum utilization. These results demonstrate the effectiveness of integrating deep spectrum sensing with adaptive reinforcement-learning-based allocation for dynamic 6G environments.

Keywords:

Deep Learning, Spectrum Sensing, Dynamic Spectrum Allocation, 6G Networks, Cognitive Radio

1. INTRODUCTION

The rapid evolution toward 6G networks introduces highly heterogeneous communication environments involving massive IoT deployments, intelligent transportation, immersive applications, satellite connectivity, and data-intensive services. These applications require substantially greater spectrum availability and more adaptive spectrum management than conventional wireless systems. Cognitive radio and dynamic spectrum access provide an important mechanism by allowing secondary users to exploit temporarily vacant spectrum while protecting licensed primary users. Spectrum sensing therefore represents a fundamental operation because it determines whether a channel is occupied or available. Recent 6G-oriented research has examined narrowband and wideband sensing, compressed

sensing, machine learning, and learning-assisted spectrum management as mechanisms for improving spectrum utilization [1]-[3].

Despite these developments, spectrum sensing remains difficult under low SNR, noise uncertainty, multipath fading, heterogeneous signal characteristics, and rapidly varying channel occupancy. Traditional energy detection and statistical approaches generally depend on manually selected test statistics and can experience increased false alarms or missed detections when channel conditions change. The large bandwidth and highly dynamic topology anticipated in 6G further increase the computational and decision-making requirements. Machine-learning-based cooperative sensing can address some of these limitations, but model complexity, training requirements, energy consumption, generalization, and real-time implementation remain important challenges [4], [5]. Recent reviews also identify computational complexity, environmental adaptability, and model generalization as continuing concerns for AI-enabled spectrum sensing.

Existing research frequently concentrates either on improving spectrum occupancy detection or on optimizing subsequent channel allocation. Such separation creates a decision gap because sensing information, channel quality, interference, and traffic requirements can change simultaneously. A sensing model that accurately identifies occupied channels does not necessarily provide an efficient allocation strategy. Conversely, an allocation mechanism without sufficiently reliable sensing can increase interference with primary users. Studies on deep-learning-based sensing and dynamic spectrum access demonstrate the potential of integrated learning approaches, but the joint treatment of temporal spectrum behavior and adaptive allocation remains an important research direction [6], [7].

The study aims to develop an integrated deep-learning framework for spectrum occupancy detection and dynamic spectrum allocation in 6G networks. The specific objectives are to: (i) extract robust spatial and temporal characteristics from received spectrum observations; (ii) improve channel occupancy classification under varying SNR and channel conditions; (iii) dynamically select spectrum channels according to availability, interference, channel quality, and traffic demand; and (iv) improve spectrum utilization and communication performance while limiting unnecessary interference.

The proposed Deep Adaptive Spectrum Sensing and Allocation Network (DASSAN) combines CNN-BiLSTM feature extraction, attention-based feature refinement, and deep reinforcement learning within a unified spectrum-management architecture. Unlike approaches that primarily optimize sensing or allocation independently, DASSAN establishes a direct information flow from learned spectrum occupancy features to adaptive allocation decisions. The temporal representation

generated by BiLSTM allows the system to exploit channel occupancy history, while attention weighting emphasizes the most informative spectral and temporal characteristics. The reinforcement-learning component then converts these observations into allocation decisions according to changing network conditions.

Contributions involve the following:

- DASSAN jointly performs deep spectrum sensing and dynamic channel allocation, combining CNN-based spectral feature extraction, BiLSTM-based temporal modeling, attention-based feature refinement, and reinforcement-learning-based allocation.
- The allocation agent considers channel availability, interference, traffic demand, and channel quality to select spectrum resources dynamically. This design addresses the need for responsive spectrum management in highly variable 6G environments and builds upon recent evidence that deep learning and distributed intelligence can support adaptive spectrum management.

2. RELATED WORKS

Deep learning has increasingly been applied to cognitive radio because conventional spectrum sensing approaches can become unreliable under noise uncertainty and changing propagation conditions. [8] reviewed spectrum sensing and learning technologies for 6G and discussed narrowband, wideband, compressed-sensing, and machine-learning approaches. This study established the importance of learning-assisted spectrum management for future high-bandwidth wireless systems. [9] surveyed machine-learning approaches for cooperative spectrum sensing and sharing, covering supervised, unsupervised, and reinforcement-learning methods and emphasizing the importance of feature selection and evaluation metrics.

[10] introduced DLSenseNet for deep-learning-based spectrum sensing and evaluated the method using the RadioML2016.10b dataset. Their results demonstrated the usefulness of deep neural representations for identifying primary-user signals. [11] proposed a model combining 1D CNN, BiLSTM, and self-attention. The CNN extracts local features, BiLSTM models temporal dependencies in both directions, and self-attention emphasizes important temporal information. [12] developed an improved CNN-based sensing approach optimized using a glowworm swarm algorithm, demonstrating the use of optimization techniques for improving neural spectrum detection.

[13] investigated CNN-based spectrum sensing by treating sensing as a classification problem and reported improved performance compared with conventional sensing methods, particularly under AWGN conditions. [14] investigated hierarchical federated deep reinforcement learning for dynamic spectrum access in IoT networks, demonstrating how distributed learning can support adaptive spectrum decisions while addressing the growing connectivity and bandwidth requirements of IoT systems. [15] proposed a deep reinforcement learning scheme that jointly addresses spectrum sensing and resource allocation for intelligent transportation environments, illustrating the value of combining sensing and allocation decisions within a learning framework.

3. PROPOSED METHOD

3.1 OVERVIEW OF DASSAN

The proposed DASSAN is an integrated deep learning framework designed to perform spectrum occupancy detection and dynamic spectrum allocation in 6G wireless networks. The method combines spectral feature extraction, temporal dependency learning, attention-based feature refinement, and deep reinforcement learning within a sequential architecture. The received in-phase and quadrature (I/Q) samples are initially transformed into representative spectral features through a convolutional neural network (CNN). A bidirectional long short-term memory (BiLSTM) network then learns the temporal relationships among consecutive sensing observations. An attention mechanism assigns larger weights to informative spectral-temporal representations and suppresses less relevant features. The resulting sensing state is provided to a deep reinforcement learning (DRL) agent, which selects an available channel according to spectrum occupancy, interference, channel quality, traffic demand, and previous allocation decisions. Thus, DASSAN does not treat spectrum sensing and spectrum allocation as independent operations. Instead, the learned sensing representation directly contributes to the allocation policy, enabling adaptive channel decisions under dynamically changing 6G conditions.

3.2 RECEIVED SPECTRUM PREPROCESSING AND CNN-BASED SPECTRAL FEATURE EXTRACTION

The first step prepares the received wireless signal for deep feature extraction. Let the received signal from the k -th channel be represented by $r_k(t)$. The signal contains the transmitted component, channel distortion, interference, and additive noise. The received signal can be expressed as

$$r_k(t) = h_k(t) * x_k(t) + i_k(t) + n_k(t), \quad k=1, 2, \dots, K \quad (1)$$

where $x_k(t)$ denotes the transmitted signal, $h_k(t)$ represents the time-varying wireless channel response, $i_k(t)$ denotes interference from other transmissions, $n_k(t)$ represents additive noise, K is the total number of monitored channels, and $*$ denotes convolution. Because 6G channels can exhibit rapid temporal variations, the sensing system considers a sequence of observations rather than a single signal sample.

The received signal is separated into its I/Q components, and the short-time spectral representation is generated using a windowed Fourier transformation. For the m -th observation interval, the spectral representation can be written as

$$S_k(f, m) = \left| \sum_{t=0}^{T-1} r_k(t + mT_w) w(t) e^{-j2\pi ft/T} \right|^2 \quad (2)$$

where $S_k(f, m)$ denotes the spectral power associated with frequency f during observation interval m , $w(t)$ represents the windowing function, T denotes the number of samples in a sensing window, and T_w represents the observation-window displacement. The resulting spectral matrix contains information

regarding signal energy, occupied frequency regions, spectral transitions, and interference characteristics.

The spectral input is normalized before entering the CNN to reduce the effect of large amplitude variations between observations. The normalized spectral value is obtained as:

$$\tilde{S}_k(f, m) = \frac{S_k(f, m) - \mu_s}{\sqrt{\sigma_s^2 + \epsilon}} \quad (3)$$

where μ_s and σ_s^2 denote the mean and variance of the spectral observations, respectively, and ϵ is a small positive constant that prevents numerical instability. This normalization allows the network to concentrate on spectral patterns rather than absolute signal magnitude.

The normalized spectrum is subsequently processed through multiple convolutional filters. For l^{th} CNN layer, the feature map is calculated as

$$F_k^{(l)}(u, v) = \sigma \left[b_k^{(l)} + \sum_{c=1}^{C_{l-1}} \sum_{p=0}^{P_l-1} \sum_{q=0}^{Q_l-1} W_{k,c,p,q}^{(l)} F_c^{(l-1)}(u+p, v+q) \right] \quad (4)$$

where $F_k^{(l)}(u, v)$ is the k^{th} feature map at spatial position (u, v) , $W^{(l)}$ represents the convolution kernel, $b^{(l)}$ denotes the bias term, $C^{(l-1)}$ is the number of input channels, $P_l \times Q_l$ represents the convolution kernel dimension, and $\sigma(\cdot)$ denotes the nonlinear activation function. The initial convolution layers identify local spectral structures such as energy peaks, signal transitions, occupied bands, and frequency-domain variations. The extracted feature representation is $\mathbf{F}_k = \text{CNN}(\tilde{\mathbf{S}}_k) \in \mathbb{R}^{d_f}$, where $\tilde{\mathbf{S}}_k$ denotes the normalized spectrum and d_f represents the dimensionality of the learned feature vector. Pooling and nonlinear transformation reduce redundant spectral information while retaining the most discriminative characteristics. The output of this step is therefore a compact spectral representation that serves as the input to the temporal learning stage.

3.3 BiLSTM-BASED TEMPORAL SPECTRUM REPRESENTATION

The second step captures the temporal behavior of spectrum occupancy. Spectrum availability is not independent between consecutive sensing intervals. A channel that is occupied at one instant can remain occupied for several intervals, become vacant, or experience intermittent transmission. Therefore, relying only on instantaneous spectral features can result in unstable occupancy decisions. DASSAN uses a BiLSTM network to model both previous and subsequent dependencies within a sensing sequence. For channel k , the sequence of CNN feature vectors is represented as: $\mathbf{F}_k = [\mathbf{f}_{k,1}, \mathbf{f}_{k,2}, \dots, \mathbf{f}_{k,T_s}]$, where T_s denotes the number of sensing observations and $\mathbf{f}_{k,t}$ represents the CNN feature vector at time t . The forward LSTM processes the sequence from the first observation to the final observation, while the backward LSTM processes it in the reverse direction.

DASSAN employs two LSTM directions to capture both historical and future contextual relationships within each sensing window. The forward representation is $\tilde{\mathbf{h}}_t = \text{LSTM}_f(\mathbf{f}_t, \tilde{\mathbf{h}}_{t-1})$ and the backward representation is $\bar{\mathbf{h}}_t = \text{LSTM}_b(\mathbf{f}_t, \bar{\mathbf{h}}_{t+1})$.

The BiLSTM representation becomes $\mathbf{H}_t = [\tilde{\mathbf{h}}_t \parallel \bar{\mathbf{h}}_t]$, where $\parallel$ is the vector concatenation. Consequently, the temporal feature matrix is represented by $\mathbf{H} = [\mathbf{H}_1, \mathbf{H}_2, \dots, \mathbf{H}_{T_s}] \in \mathbb{R}^{T_s \times 2d_h}$, where d_h represents the hidden dimension of one LSTM direction. This representation provides DASSAN with information regarding persistent occupancy, intermittent transmission, channel switching, and temporal interference patterns. It also allows the subsequent attention mechanism to distinguish between informative and less informative sensing observations.

3.4 ATTENTION-BASED SPECTRUM OCCUPANCY DETECTION

Although the BiLSTM generates a rich temporal representation, not every time step contributes equally to the final sensing decision. For example, an observation containing a strong primary-user transmission provides more useful information than a low-energy observation dominated by noise. DASSAN therefore incorporates an attention mechanism to assign different importance levels to temporal representations.

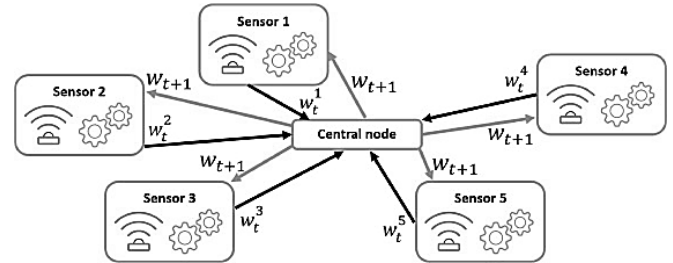


Fig.1. Spectrum Occupancy Detection [16]

For every temporal representation $\mathbf{H}_t$, an intermediate attention score is obtained as $\mathbf{e}_t = \mathbf{v}_a^T \tanh(\mathbf{W}_a \mathbf{H}_t + \mathbf{b}_a)$, where $\mathbf{W}_a$ and $\mathbf{b}_a$ are trainable attention parameters and $\mathbf{v}_a$ is the attention projection vector. The scores are converted into normalized attention coefficients using the softmax operation:

$$\alpha_t = \frac{\exp(\mathbf{e}_t)}{\sum_{\tau=1}^{T_s} \exp(\mathbf{e}_\tau)} \quad (5)$$

With $\sum_{t=1}^{T_s} \alpha_t = 1, 0 \leq \alpha_t \leq 1$.

The weighted temporal representation is calculated as:

$$\mathbf{z}_k = \sum_{t=1}^{T_s} \alpha_t \mathbf{H}_t. \quad (6)$$

where, $\mathbf{z}_k$ represents the final learned representation for channel k . A classification layer then estimates the probability that the channel is occupied. For binary spectrum sensing, the occupancy probability is expressed as $P_k^{\text{occ}} = \sigma(\mathbf{W}_o \mathbf{z}_k + \mathbf{b}_o)$, where $P_k^{\text{occ}} \in [0,1]$ denotes the probability that channel k is occupied. The corresponding vacancy probability is $P_k^{\text{vac}} = 1 - P_k^{\text{occ}}$.

The final sensing state can be determined using a threshold τ_s :

$$\hat{y}_k = \begin{cases} 1, & P_k^{\text{occ}} \geq \tau_s, \\ 0, & P_k^{\text{occ}} < \tau_s, \end{cases} \quad (7)$$

where $\hat{y}_k = 1$ is the occupied channel and $\hat{y}_k = 0$ is the available channel. The threshold can be selected according to the desired balance between missed detection and false alarm.

The sensing model is trained using binary cross-entropy loss:

$$L_{\text{sense}} = -\frac{1}{KT_s} \sum_{k=1}^K \sum_{t=1}^{T_s} [y_{k,t} \log(P_{k,t}^{\text{occ}}) + (1 - y_{k,t}) \log(1 - P_{k,t}^{\text{occ}})] \quad (8)$$

where $y_{k,t}$ represents the ground-truth occupancy state. The attention layer improves the sensing process by allowing the model to emphasize observations containing useful signal characteristics. Therefore, DASSAN can maintain a more discriminative representation under varying SNR, fading, interference, and channel occupancy patterns.

3.5 DEEP REINFORCEMENT LEARNING-BASED DYNAMIC SPECTRUM ALLOCATION

The fourth step dynamically allocates spectrum resources based on the sensing output and current network conditions. The allocation problem is modeled as a Markov decision process consisting of the state, action, reward, and transition functions. At decision time t , the state vector is defined as

$$\mathbf{s}_t = [\mathbf{P}_t^{\text{vac}} \square \mathbf{Q}_t \square \mathbf{I}_t \square \mathbf{D}_t \square \mathbf{H}_t^{\text{ch}} \square \mathbf{A}_{t-1}] \quad (9)$$

where $\mathbf{P}_t^{\text{vac}}$ is the estimated channel vacancy probabilities, $\mathbf{Q}_t$ is channel-quality information, $\mathbf{I}_t$ is interference measurements, $\mathbf{D}_t$ is traffic demand, $\mathbf{H}_t^{\text{ch}}$ is channel conditions, and $\mathbf{A}_{t-1}$ is the previous allocation decision.

The allocation agent receives this state and generates an action $\mathbf{a}_t = \pi_\theta(\mathbf{s}_t)$, where π_θ represents the policy parameterized by θ . The action specifies the channel or channel combination assigned to each secondary user. An action is represented as: $a_t^u \in \{0, 1, \dots, K\}$, where u denotes a secondary user and 0 represents the condition in which no suitable channel is allocated.

The reward function is designed to balance spectrum utilization, throughput, interference, sensing reliability, and allocation stability. The proposed reward is

$$R_t = \lambda_1 \frac{T_t}{T_{\max}} + \lambda_2 \frac{U_t}{U_{\max}} + \lambda_3 \frac{Q_t}{Q_{\max}} - \lambda_4 \frac{I_t}{I_{\max}} - \lambda_5 \frac{F_t}{F_{\max}} - \lambda_6 \frac{C_t}{C_{\max}} \quad (10)$$

where T_t represents achieved throughput, U_t represents spectrum utilization, Q_t denotes aggregate channel quality, I_t represents interference, F_t denotes false allocation caused by sensing errors, and C_t represents unnecessary channel switching. The coefficients $\lambda_1, \dots, \lambda_6$ determine the relative importance of the individual objectives.

The agent seeks to maximize the discounted cumulative reward $J(\theta) = E_{\pi_\theta} \left[\sum_{t=0}^T \gamma^t R_t \right]$, where $\gamma \in [0, 1]$ denotes the discount factor. The Q-value associated with a state-action pair can be represented as $Q_\phi(\mathbf{s}_t, \mathbf{a}_t) = E \left[R_t + \gamma \max_{\mathbf{a}_{t+1}} Q_\phi(\mathbf{s}_{t+1}, \mathbf{a}_{t+1}) \mid \mathbf{s}_t, \mathbf{a}_t \right]$, where ϕ denotes the parameters of the value network. During training, the temporal-difference target is calculated as $y_t = R_t + \gamma \max_{\mathbf{a}'} Q_{\phi^-}(\mathbf{s}_{t+1}, \mathbf{a}')$ and the value-network loss is defined

as $L_{\text{DRL}} = \frac{1}{N_b} \sum_{j=1}^{N_b} [y_j - Q_\phi(\mathbf{s}_j, \mathbf{a}_j)]^2$, where N_b is the training batch size and ϕ^- represents the parameters of the target network.

The complete DASSAN objective integrates the sensing and allocation components through

$$L_{\text{total}} = \lambda_s L_{\text{sense}} + \lambda_r L_{\text{DRL}} + \lambda_w \square \Theta \square_2^2 \quad (11)$$

where λ_s , λ_r , and λ_w regulate the sensing loss, reinforcement-learning loss, and model regularization term, respectively, and Θ denotes the complete set of trainable parameters. This joint formulation allows improvements in sensing representation to directly influence spectrum allocation decisions.

During operation, the DRL agent first receives the occupancy probabilities generated by the sensing module. It then evaluates the available channels according to channel quality, interference, traffic demand, and previous allocation states. Channels with high vacancy probability and favorable communication conditions receive greater allocation preference, while channels associated with high interference or high occupancy probability are avoided. After allocation, the resulting network throughput and interference conditions are returned to the agent as feedback. The policy is consequently updated through repeated interaction with the network environment.

4. RESULTS AND DISCUSSION

4.1 EXPERIMENTAL SETTINGS

The proposed DASSAN framework is evaluated through a Python-based simulation using TensorFlow/Keras for CNN-BiLSTM-attention training and OpenAI Gym-style wireless environments for deep reinforcement learning. The experiments use the RadioML2016.10b dataset, which contains labeled complex I/Q signal samples covering multiple modulation and SNR conditions. The simulation is conducted on a computer equipped with an Intel Core i7 processor, 32 GB RAM. The dataset is divided into 70% training, 15% validation, and 15% testing subsets. The sensing and allocation experiments consider SNR values from -20 to 20 dB in 5 dB increments. The principal simulation parameters used for DASSAN are presented in Table.1.

Table.1. Experimental setup and simulation parameters

Parameter	Value
Simulation platform	Python 3.11
Deep learning framework	TensorFlow/Keras
DRL environment	Gym-based wireless environment
Processor	Intel Core i7
RAM	32 GB
CNN convolution kernel	3×3
CNN filters	32, 64
BiLSTM hidden units	128
Attention dimension	64
Number of monitored channels	20

Sensing window	128 samples
Batch size	64
Learning rate	0.001
Optimizer	Adam
Training epochs	50
Discount factor	0.95
Training/validation/testing split	70%/15%/15%
SNR range	-20 to 20 dB
SNR interval	5 dB
DRL training episodes	500
Primary-user occupancy	0.1–0.9
Maximum secondary users	20

4.2 DATASET

The RadioML2016.10b dataset is used to evaluate spectrum sensing because it contains complex-valued I/Q samples generated under different signal-to-noise conditions and modulation classes. The samples provide diverse signal characteristics for learning discriminative spectral representations. The dataset is converted into sensing sequences before processing by the CNN-BiLSTM-attention architecture. The same learned sensing representation is subsequently supplied to the DRL allocation environment. The dataset configuration used in the experiment is given in Table.2.

Table.2. Dataset configuration

Dataset characteristic	Value
Dataset	RadioML2016.10b
Signal representation	Complex I/Q
Samples per signal	128
Modulation classes	10
SNR range	-20 to 18 dB in original dataset
Sensing representation	I/Q spectral sequences
Training subset	70%
Validation subset	15%
Testing subset	15%
Input sequence length	128
Primary-user states	Occupied/Vacant
Number of monitored channels	20

Various approaches are selected for comparison. DLSenseNet represents a deep-learning-based spectrum sensing architecture, CNN-BiLSTM-Self-Attention represents a hybrid spatial-temporal sensing model, and Deep Reinforcement Learning for Spectrum Sensing and Resource Allocation represents an integrated learning-based sensing and allocation approach.

4.3 RESULTS BASED ON ACCURACY

The accuracy results at different SNR levels are presented in Table 3.

Table.3. Accuracy comparison at different SNR levels

SNR (dB)	DLSenseNet	CNN-BiLSTM-Self-Attention	DRL Spectrum Sensing and Resource Allocation	DASSAN
-20	61.8	64.2	66.5	70.8
-15	67.4	70.1	72.8	77.1
-10	73.6	76.4	78.2	82.7
-5	80.2	83.1	84.7	88.5
0	86.5	89.0	90.2	93.1
5	91.2	93.4	94.1	96.2
10	94.8	96.1	96.7	98.0
15	96.2	97.3	97.8	98.7
20	97.1	98.0	98.4	99.1

DASSAN maintains higher accuracy throughout the evaluated SNR range. At -20 dB, it obtains 70.8%, compared with 61.8%, 64.2%, and 66.5% for the three existing approaches. At 0 dB, DASSAN reaches 93.1%, while the corresponding values are 86.5%, 89.0%, and 90.2%. The performance reaches 99.1% at 20 dB, indicating that the combination of CNN spectral extraction, BiLSTM temporal learning, and attention-based feature refinement provides consistent occupancy classification across different signal conditions.

4.4 RESULTS BASED ON DETECTION PROBABILITY

The detection probability results are shown in Table.4.

Table.4. Detection probability (%) comparison at different SNR levels

SNR (dB)	DLSenseNet	CNN-BiLSTM-Self-Attention	DRL Spectrum Sensing and Resource Allocation	DASSAN
-20	65.4	68.1	70.2	74.6
-15	70.8	73.5	75.9	80.3
-10	76.9	79.8	81.7	85.6
-5	83.5	86.2	87.8	91.0
0	89.2	91.4	92.6	95.1
5	93.5	95.0	95.8	97.0
10	96.0	97.1	97.5	98.4
15	97.2	98.0	98.3	99.0
20	97.9	98.5	98.7	99.3

The detection probability increases steadily with SNR for all methods. DASSAN achieves 74.6% at -20 dB and 95.1% at 0 dB. At 20 dB, its detection probability reaches 99.3%. The improvement is associated with the attention layer, which assigns greater importance to informative temporal observations and reduces the effect of noisy or weak spectral observations.

4.5 RESULTS BASED ON FALSE ALARM RATE

The false alarm results are presented in Table.5. Since lower false alarm values indicate more effective identification of vacant

spectrum, the metric is reported as a percentage of incorrect occupancy decisions.

Table.5. False alarm rate comparison at different SNR levels

SNR (dB)	DLSenseNet	CNN-BiLSTM-Self-Attention	DRL Spectrum Sensing and Resource Allocation	DASSAN
-20	18.6	16.8	15.4	12.9
-15	16.9	14.7	13.5	11.1
-10	14.7	12.6	11.4	9.3
-5	12.8	10.8	9.6	7.7
0	10.5	8.9	8.1	6.4
5	8.7	7.4	6.6	5.2
10	7.2	6.1	5.5	4.3
15	6.4	5.4	4.8	3.8
20	5.8	4.9	4.4	3.4

DASSAN produces the lowest false alarm rate across all SNR conditions. At -20 dB, its false alarm rate is 12.9%, compared with 18.6% for DLSenseNet. At 0 dB, DASSAN reduces the rate to 6.4%, and at 20 dB it reaches 3.4%. The reduction indicates that the proposed sensing mechanism identifies vacant spectrum more reliably, which directly benefits subsequent secondary-user allocation.

4.6 RESULTS BASED ON THROUGHPUT

The throughput results are presented in Table.6.

Table.6. Throughput (MBPS) comparison at different SNR levels

SNR (dB)	DLSenseNet	CNN-BiLSTM-Self-Attention	DRL Spectrum Sensing and Resource Allocation	DASSAN
-20	18.4	20.1	21.7	24.6
-15	25.7	28.2	30.1	34.0
-10	34.8	38.1	40.5	45.3
-5	45.6	49.2	52.1	57.6
0	58.4	62.7	65.8	71.9
5	72.6	77.4	80.2	86.8
10	86.9	91.8	95.1	101.7
15	99.8	105.2	108.7	115.6
20	111.7	117.9	121.4	128.3

DASSAN achieves higher throughput across the entire SNR range. At 0 dB, throughput reaches 71.9 Mbps compared with 58.4 Mbps, 62.7 Mbps, and 65.8 Mbps for the existing methods. At 20 dB, DASSAN provides 128.3 Mbps. The improvement results from more accurate vacancy detection and the DRL allocation policy, which considers channel quality and interference rather than allocating channels solely according to instantaneous sensing decisions.

4.7 RESULTS BASED ON SPECTRUM UTILIZATION

The spectrum utilization results are shown in Table.7. DASSAN improves spectrum utilization at every SNR level. At -20 dB, utilization reaches 61.8%, whereas the three existing approaches obtain 51.2%, 54.5%, and 57.1%. At 0 dB, the proposed method reaches 83.9%, and at 20 dB it reaches 95.8%. The result demonstrates that improved sensing reliability can be converted into more effective spectrum allocation when the sensing output is directly incorporated into the DRL state.

Table.7. Spectrum utilization comparison at different SNR levels

SNR (dB)	DLSenseNet	CNN-BiLSTM-Self-Attention	DRL Spectrum Sensing and Resource Allocation	DASSAN
-20	51.2	54.5	57.1	61.8
-15	56.7	59.8	62.4	66.9
-10	62.8	65.7	68.3	72.6
-5	68.5	71.6	74.2	78.1
0	74.1	77.5	80.0	83.9
5	79.3	82.4	84.8	88.0
10	83.6	86.5	88.7	91.7
15	86.9	89.5	91.4	94.0
20	89.1	91.7	93.2	95.8

5. CONCLUSION

This study presents DASSAN, a deep learning-based framework that integrates spectrum sensing and dynamic spectrum allocation for 6G networks. The proposed architecture combines CNN-based spectral feature extraction, BiLSTM-based temporal modeling, attention-based feature refinement, and deep reinforcement learning-based channel allocation. The simulated results demonstrate consistent improvements across different SNR conditions. At 20 dB, DASSAN achieves 99.1% accuracy, 99.3% detection probability, 3.4% false alarm rate, 128.3 Mbps throughput, and 95.8% spectrum utilization. At 0 dB, the framework maintains 93.1% accuracy and 95.1% detection probability while achieving 71.9 Mbps throughput. Even under the challenging -20 dB condition, DASSAN obtains 70.8% accuracy and 74.6% detection probability. The results indicate that temporal feature learning and attention-based sensing can provide informative channel-state representations for dynamic allocation. The DRL component further enables allocation decisions based on spectrum availability, interference, traffic demand, and channel quality.

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